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Fuzzy logic applied to simultaneous selection of sweet potato genotypes

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ABSTRACT

The objective of this work was to perform simultaneous selection in sweet potato genotypes and to verify the efficiency of fuzzy systems when compared to the Mulamba & Mock (MM) method. The experiment was carried out in randomized blocks, with 24 sweet potato genotypes, four replications and ten plants per plot. The breeding values were obtained by the mixed model methodology (REML/BLUP), and then the MM index and the gains obtained by the developed fuzzy systems were estimated. There was a predominance of environmental effects over genotypic effects for all traits. These estimates suggest an expressive contribution of the environment for these traits and, consequently, greater difficulty for genetic improvement. Through this, the fuzzy systems stood out in relation to the MM method, as they presented superior selection gains for characters related to human and animal food. The genotypes with potential for human and animal food selected by the fuzzy system were: UFVJM07, UFVJM05, UFVJM09, UFVJM40, UFVJM01, UFVJM25, UFVJM15. The fuzzy logic was efficient in the simultaneous selection of sweet potato genotypes, allowing the selection of plants similar to the desirable ideotype than the MM method.

Keywords: *Ipomoea batatas*, multiple selection,computational intelligence.

RESUMO

Lógica fuzzy aplicada à seleção simultânea de genótipos de batata-doce

O objetivo deste trabalho foi realizar a seleção simultânea em genótipos de batata-doce e verificar a eficiência de sistemas fuzzy quando comparados ao método Mulamba & Mock (MM). O experimento foi em blocos casualizados, com 24 genótipos de batata-doce, quatro repetições e dez plantas por parcela. Os valores genéticos foram obtidos pela metodologia dos modelos mistos (REML/BLUP), e posteriormente estimados o índice MM e os ganhos obtidos pelos sistemas fuzzy desenvolvidos. Houve predomínio de efeitos ambientais sobre os efeitos genotípicos para todas as características. Essas estimativas sugerem expressiva contribuição do ambiente para esses caracteres e, consequentemente, maior dificuldade para o melhoramento genético. Através disso, os sistemas fuzzy se destacaram em relação ao método de MM, já que apresentaram ganhos de seleção superiores para os caracteres relacionados à alimentação humana e animal. Os genótipos com potencial para alimentação humana e animal selecionados pelo sistema fuzzy foram: UFVJM07, UFVJM05, UFVJM09, UFVJM40, UFVJM01, UFVJM25, UFVJM15. A lógica fuzzy foi eficiente na seleção simultânea de genótipos de batata-doce, permitindo a seleção de plantas semelhantes ao ideótipo desejável do que o método MM.

Palavas-chave: *Ipomoea batatas*, seleção múltipla, inteligência computacional.

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The sweet potato (*Ipomoea batatas*) is a vegetable belonging to the Convolvulaceae family, with tuberous roots and originating in Tropical America. This crop stands out for its rusticity, easy cultivation, wide adaptation to environmental adversities and low cultivation cost (Andrade Júnior *et al.*, 2012). It is a rich source of sugars, carbohydrates, minerals and vitamins, making it an important alternative in human and animal food (Vargas *et al.*, 2017), as well as being a raw material for food, textile, paper, cosmetics and ethanol industries, among others (Cardoso *et al.*, 2005).

The vegetable has great socioeconomic importance, has high yield potential and a wide genotypic and phenotypic variety (Otoboni *et al.*, 2020). In this sense, efforts for the genetic improvement of the crop are necessary, aiming at increasing the productivity and quality of the roots. In this way, it is necessary to select better individuals than pre-existing ones, considering several characteristics simultaneously (Azevedo *et al.*, 2014). Among the simultaneous selection methods, stands out the selection index based on the sum of ranks (Rosado *et al.*, 2012; Luz *et al.*, 2018), proposed by Mulamba & Mock (1978). However, there are still few researches relating the use of indexes in the simultaneous selection of characters with a pre-established marketable standard.

In this sense, the use of computational intelligence can become a potential alternative for plant breeding (Carneiro *et al.*, 2018). One of the intelligence techniques that can be employed is the fuzzy logic which allows working with quantitative and qualitative data simultaneously (Pang & Bai, 2013; Casillas *et al.*, 2013). Through this model, it is possible to translate verbal expressions, generally imprecise and from experts, into numerical values (Papadopoulos *et al.*, 2011), which makes computational automation possible in several areas such as the classification of the best genotypes. This allows for the automation of classifications by computer systems quickly and accurately. Its use in plant genetic improvement is recent, but some research demonstrate efficiency in the use of fuzzy logic to automate the adaptability and stability of plants (Carneiro *et al.*, 2019), in the selection of colored fiber cotton genotypes based on stability and adaptability (Cardoso *et al.*, 2021), as well as for cultivar recommendation (Carneiro *et al.*, 2018).

In view of the above, the objective was to perform simultaneous selection on sweet potato genotypes and to verify the efficiency of fuzzy systems for this purpose when compared to the Mulamba & Mock methodology.

MATERIAL AND METHODS

Installation and evaluation of the field experiment

The experiment was conducted at the Institute of Agricultural Sciences (UFMG-ICA) Campus Montes Claros-MG (16°40'58"S; 43°50'20"W).

The seedlings were produced from cuttings, approximately 20 cm long, of the branches of 24 genotypes from the sweet potato germplasm selected by experiments (Andrade Júnior *et al.*, 2012; Viana *et al.*, 2011). The seedlings were kept in polyethylene pots with commercial substrate for 15 days for rooting, irrigated daily, and later were taken to field.

The field experiment was conducted in a randomized complete block design with 24 treatments (genotypes) and four replications, spacing of 1 m between plots and ten plants per plot, plants spaced 0.30 m. The treatments consisted of the genotypes UFVJM (01, 05, 06, 07, 09, 15, 21, 25, 28, 29, 31, 37, 40, 41, 44, 54 and 56), Brazilândia Roxa, Belgard, Arruba, Cambraia, Cariru Vermelho, Princesa and T Carro 01. The preparation of the area, fertilization and cultivation were performed as recommended for the crop (Filgueira, 2008).

Harvest was carried out six months after planting, when the branches were cut close to the soil, while the roots were harvested manually with the aid of hoes. The branches and roots were weighed and separated in order to evaluate production and quality traits. The green mass yield of the branches and total root yield were obtained by weighing (t ha^{-1}). The dry matter content of branches and leaves and dry matter content of roots (DMR) were obtained by collecting samples of approximately 200 g, conditioned in kraft paper and dried in an oven with forced air circulation at 65ºC until constant weight (Andrade Júnior *et al.*, 2012). The dry matter yield of branches was obtained by the product between green mass yield and dry matter content of the branches and leaves (t ha^{-1}).

For marketable root yield, we considered only roots weighing between 100 and 800 g, without veins, greenish or not attacked by pests, without cracks and not deformed (t ha^{-1}) (Andrade Júnior *et al.*, 2012). The average marketable root mass was obtained by the ratio between marketable root yield and total number of roots with marketable standards in each plot (kg). The weight of not marketable roots was used to estimate the waste yield.

Regarding root shape (RSH) and resistance to soil insects (RI), three evaluators awarded grades, with the final value being expressed by means of the three grades. These vary from 1 to 5 (Azevedo *et al.*, 2002), given at plot level, in which grade 1 = root with fusiform, regular shape, without veins or any kind of cracks; grade 2 = predominantly fusiform, but with some unevenness, possible presence of veins or curvatures in the roots; grade 3 = irregular shape, non-fusiform, with some veins/cracks, but commercially acceptable; grade 4 = very irregular shape, with veins and cracks, commercially undesirable; and grade 5 = totally out of marketable standards, very irregular and deformed, with many veins and cracks.

The resistance to soil insects was assigned as follows (Azevedo *et al.*, 2002): grade 1 = roots free of insect damage, with desirable commercial aspect; grade 2 = roots with little damage, but with the presence of some galleries and holes; grade 3 = roots with very noticeable damages (presence of gallery and holes in greater quantity), with impaired commercial aspect; grade 4 = roots with many damages, unsuitable for commercialization (presence of many galleries, holes and beginning of decay); and grade 5 = roots unsuitable for commercial purposes (filled with galleries, holes and more advanced rot).

Configuration and use of fuzzy logic

Fuzzy logic was adopted in order to automate the process of simultaneous selection of characters for the desired marketable standard for the sweet potato crop. Since it allows the representation of propositions expressed in a natural language (Zadeh, 1988), that is, the modeling of the breeder's experience. Thus, for the descriptors analyzed, the fuzzy controller developed was based on the fuzzy inference system proposed by Mamdani & Assilian (1975). For this, the input fuzzy linguistic variables used were the desirable commercial ranges for each characteristic. Thus, fuzzy sets were generated for each variable through membership functions that allowed, through the "fuzzification" process, the classification of each descriptor analyzed as commercially desirable or not.

For this, the descriptors were grouped into three systems, the first one named HF, related to human feeding, and considers the traits of marketable root yield, average marketable root mass, root dry matter content, shape and insect resistance. The second system, related to animal feeding (AF), considered the dry mass yield of branches, the marketable roots yield and the waste yield. All these input variables of the AF and HF systems (phenotypic values) were standardized for zero means and one unit of standard deviations. This was done by subtracting the phenotypic values from the mean, and then dividing by the standard deviation of the trait. This standardization is important to not have the influence of different scales on the results. The output of the two fuzzy systems was used as input to a third system called FIM, allowing the achievement of a general score for the plot (Figure 1).

In the fuzzification step, for all characteristics, the values were allocated into Fuzzy sets categorized as "too bad", "bad", "good" and "very good" by means of trapezoidal membership functions (Equation 1):

$$trapmf(x; a, b, c, d) = max\left(min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right)$$

where: *x* input variable; *a, b, c, d* are abscissa of the four vertices of the trapezoid formed by the membership function (parameters arbitrated); *max* is maximum inference value; *min* is minimum inference value. The trapezoidal function is useful when you have a commercial range within which individuals are equally desirable.

To characterize the input and output characteristics of systems related to human food (HF), animal (AF) and the input and output of the FIM system, the parameters were arbitrated in five linguistic variables (Figure 2A): too bad (a=-5, b=-5, c=-0.755, d=-0.598), bad (a=-0.755, b=-0.598, c=-0.063, d=0.063), good (a=-0.063, b=0.063, c=0.598, d=0.755) and very good (a=0.598, b=0.755, c=5, d=5). For the output variables of the HF and AF systems and the input and output of the FIM system, the parameters were arbitrated in five linguistic variables (Figure 2B): too bad (a=0, b=0, c=0.125, d=1.125), bad (a=0.125, b=1.125, c=1.375, d=2.375), average (a=1.375, b=2.375, c=2.625, d=3.625), good (a=2.625, b=3.625, c=3.875, d=4.875) and very good (a=3.875, b=4,875, c=5.0, d=5.0). These values were defined considering the cumulative probability of the standardized normal distribution. Thus, there were quartiles of 25%, 50% and 75% coincident with the intersections between the membership functions (Figure 2A).

In the inference step, the connective "and" was used, by relating the input linguistic variables with the output variable scores of each system. In each of the input classes, four scores are found, where the rules were obtained through all possible combinations between the variables used for each system and the input scores. 1024 rules were generated for HF (4^5), 64 for the AF (4^3) and 25 for FIM (5^2), using the connective "and". For each analyzed variable weights were assigned, according to the level of importance of the characteristic analyzed within the system. For the defuzzification, the centroid method was used. Next, for each fuzzy system, scores were obtained indicating the predilection of each genotype, with values varying from 1 to 5, being these criteria used as selection indexes. The fuzzy logic systems were configured and used with the aid of the package *FuzzyToolkitUoN* for the R software (R Core Team, 2019).

Estimating individual and simultaneous selection gains

For the statistical analysis of the quantitative descriptors and the scores obtained by the three fuzzy systems (using phenotypic data), we used the model y = Xr + bCov + Zg + e, in which: y is the data vector, in plots level; r is the vector of the repetition effects (assumed as fixed) added to the general means; b refers to the regression coefficient associated with the covariate (Cov) number of plants per plot; g is the vector of genotypic effects (assumed to be random); and **e** is the vector of errors (random). Capital letters represent the incidence matrices for these effects. Where: g~N(0, I) and e~N(0, I). From this model, the components of variance were estimated and the genetic values were predicted by the REML-BLUP method with the package *sommer* from the R software.

With the genetic values of each trait, the expected direct and indirect gains were estimated, selecting the best individuals (selection index of 30%). From the genetic values were obtained, for each genotype, its rank for all the traits, and, in sequence, the sum of these ranks was estimated (Mulamba & Mock index). That index consisted in classifying the genotypes for each trait in an order favorable to breeding (Dalbosco *et al.*, 2019). The genetic values obtained from the scores of the three fuzzy systems were also employed as a criterion for simultaneous selection.

To analyze the influence of the employed indexes in each of the studied variables, we estimated Pearson's correlations, with the aid of the function *cor.test* for the R software. The summary of all the steps of the methodology used is shown in Figure 3.

RESULTS AND DISCUSSION

Evaluating characters in sweet potato genotypes, higher genotypic variabilities were obtained for dry mass yield of branches (DMB), marketable roots yield (CRY) and resistance to insects (RI), with a genotypic coefficients of variation (CVg) of 26.77%, 23.77% and 20.43%, respectively (Table 1). For the other traits, the CVg varied from 5.11% for the dry matter content of roots (DMR) to 15.4% for the average weight of marketable roots (AWCR) (Table 1). The high values of CVg, observed in the present study, evidence the possibility of success in obtaining gains with the selection for this population. However, environmental variances (Ve) greater than the genotypic variance (Vg) were obtained for the observed characteristics. Thus, the superiority of the environmental coefficient of variation (CVe) should be considered for all characteristics, as well as the low index of variation (CVr), with estimates lower than 1. These estimates suggest a significant contribution of the environment to these characteristics. For the traits related to root productivity (CRY, AWCR and WASTE), these high values may be associated with the incomplete harvesting of some plots, since the roots are underground and, therefore, not visible (Azevedo *et al.*, 2015).

The CVe were found to be higher than the CVg for all the traits, and the higher values of CVe were obtained for the variables associated to root yield (CRY, AWCR and WASTE), being higher than 30% (Table 1). For the CVr, the obtained values were promising and close to 1.00 for dry matter yield of branches (0.97) and for resistance to insects (0.84). For the other traits, these values were lower than 0.63. Average heritability estimates of the genotype

(h^2mc) were found ranging from average to high for most of the traits (Table 1), being the highest values for dry mass yield of branches, resistance to insects and root shape. Heritability is directly related to the genetic gain with the selection, and may occur at the level of means, individual or plot (Azevedo *et al.*, 2015). In this sense, the highest values of h^2mc were obtained for the yield of branches dry mass and resistance to insects, demonstrating superiority of the genetic characters over the environmental ones. For the sweet potato crop, the knowledge of heritability is of fundamental importance, since the effects of dominance and epistasis are maintained in the vegetative propagation, one of the most efficient propagation systems for the crop (Gonçalves Neto *et al.*, 2012).

Genetic gains were o btained for CRY, ranging from 6.56 t ha^{-1}, for the Belgard genotype, to 13.87 t ha^{-1} for the UFVJM 40. The Belgard genotype, despite presenting low gains for CRY, presented higher gain for dry mass yield of the branches (Table 1).

The HF and AF systems showed low correlation with each other (0.147) (Table 2), demonstrating the independence between these systems. While the correlations of the HF and AF systems with the FIM system were higher, 0.807 and 0.610 respectively, indicating a positive correlation between the systems. This indicated a low association between fuzzy systems related to HF and AF, due to the different types of descriptors associated with each system. The FIM system simultaneously gathers the descriptors included in the two systems, indicating greater correlations between the FIM system and the descriptors related to human and animal food, demonstrating the efficiency of the FIM system in bringing together the descriptors included in the two systems and the possibility of using it in the simultaneous selection of characters. Comparing the agronomic descriptors of the sweet potato genotypes associated to human feeding (CRY, AWCR, DMR, RSH, RI), negative correlations were obtained for AWCR, RSH and RI and positive for CRY and DMR with the scores of the HF and FIM systems (Table 2). The FIM system allowed higher estimates of correlation with marketable root yield (0.611) and average marketable root mass (-0.449) when compared to the HF system. For the AF system, positive correlations were obtained for dry mass yield of branches (0.851) and for waste (0.861). For marketable roots yield, positive correlations were obtained with all systems (Table 2).

For human consumption, genotypes

Table 1. Genetic values for 24 sweet potato genotypes and estimation of variance components and genetic parameters of the descriptors obtained by the REML-BLUP method. Montes Claros, UFMG, 2021.

Genotype	DMB	CRY	AWCR	DMR	WASTE	RSH	RI
UFVJM25	5.76	10.77	0.30	32.53	8.92	2.78	2.18
BZ ROXA	3.16	8.84	0.34	32.38	8.62	2.72	2.95
UFVJM07	4.03	11.59	0.31	32.40	8.66	2.70	2.47
BELGARD	6.95	6.56	0.24	32.65	8.77	2.37	1.76
UFVJM31	5.15	8.68	0.27	33.74	8.78	3.03	2.31
UFVJM15	5.35	11.24	0.28	32.64	8.85	2.86	2.86
UFVJM21	4.34	10.38	0.32	32.60	8.79	2.67	2.81
ARRUBA	4.09	10.95	0.28	31.87	8.77	2.75	2.56
UFVJM28	2.81	9.47	0.40	31.87	8.67	3.30	3.32
CAMBRAIA	4.37	10.66	0.30	32.28	8.66	2.54	2.13
UFVJM05	4.42	11.26	0.30	34.84	8.72	2.78	2.37
CARIRUVERM	4.83	11.09	0.30	31.72	8.88	3.03	3.11
UFVJM44	5.48	9.23	0.29	33.32	8.80	3.18	3.05
UFVJM41	2.75	10.04	0.33	32.10	8.64	2.91	2.43
UFVJM40	4.92	13.87	0.30	32.83	8.63	2.33	1.87
UFVJM01	5.74	11.67	0.30	32.58	8.82	2.62	2.25
PRINCESA	4.59	9.92	0.28	30.92	8.83	2.85	2.93
UFVJM37	4.73	9.59	0.31	32.76	8.69	2.84	2.25
UFVJM09	4.99	11.75	0.28	32.21	8.64	2.64	2.50
T CARRO01	4.29	12.88	0.34	31.70	8.69	2.85	2.93
UFVJM06	2.18	7.90	0.31	32.78	8.59	2.38	1.89
UFVJM54	4.69	8.72	0.29	32.28	8.73	2.99	2.44
UFVJM56	4.98	8.83	0.27	33.44	8.71	2.82	1.98
UFVJM29	4.63	10.20	0.30	32.53	8.71	3.02	2.48
Vg	1.48	5.94	0.00	2.76	0.30	0.10	0.26
Ve	1.59	25.19	0.01	33.67	35.24	0.26	0.37
Vp	3.07	31.13	0.01	36.43	35.54	0.36	0.62
h^2mc	0.79	0.49	0.49	0.25	0.03	0.62	0.74
CVgi%	26.77	23.77	15.40	5.11	6.24	11.54	20.43
CVe%	27.70	48.95	31.55	17.83	67.99	18.22	24.25
CVr	0.97	0.49	0.49	0.29	0.09	0.63	0.84

DMB= dry mass yield of branches; CRY= marketable roots yield; AWCR= average weight of marketable roots; DMR= dry mass content of roots; WASTE= waste yield; RSH= root shape; RI= resistance to insects. Vg= genotypic variance; Ve= residual variance; Vf= individual phenotypic variance; h^2mc= heritability of the genotype means; CVgi%= genotypic coefficient of variation; CVe%= residual coefficient of variation; CVr= variation index.

with high yield of marketable roots, average weight of marketable roots within the standard and increases in dry mass content of roots are desirable. The decrease in grades obtained for root shape and insect resistance is extremely desirable for sweet potato, since smaller notes indicate more insect resistant and commercially accepted genotypes. Andrade Junior *et al.* (2009), analyzing 12 sweet potato genotypes, obtained scores lower than 2.5 for insect resistance and shape, indicating that the reduction in the scale of grades for these two traits is desirable when breeding this crop. On the other hand, for animal feeding, genotypes with high dry mass of branches, as well as high root yield, are ideal (waste and marketable roots). The scores of the developed FIM system correlated efficiently with the characters of interest.

The direct selection gain estimated for the DMB was the one with the highest magnitude (23.721%) (Table 3). However, it allows an unfavorable gain to the genetic improvement of the sweet potato for the yield of marketable roots (CRY). CRY showed a direct selection gain of 17.394%, allowing favorable indirect gains for most of the traits (Table 3). As evidenced by the increase in dry matter yield of branches (DMB) and dry mass content of the roots (DMR) and decreases in average weight of marketable roots (AWCR) and in the scale of grades and shapes (RSH), as well in the resistance to insects (RI) (Table 3).

The simultaneous selection for the HF system obtained the desired signals for the characteristics associated with the system, both for the Mulamba & Mock index and for the fuzzy logic (Table 3), with greater magnitudes between the fuzzy system and the marketable root production (13.656%), insect resistance (-14.857%) and RSH (-7.318%).

Regarding animal feed, favorable selection gains were obtained for DMB, CRY and WASTE (Table 3).

Table 2. Pearson's correlations between inference systems fuzzy index of HF (human feeding), AF (animal feeding), FIM (all criterions simultaneously), and between the agronomic descriptors of 24 sweet potato genotypes and the fuzzy system outputs. Montes Claros, UFMG, 2021.

Variables	HF	AF	FIM
HF	1.000	0.147	0.807
AF	0.147	1.000	0.610
FIM	0.807	0.610	1.000
DMB	0.298	0.851	0.579
CRY	0.531	0.189	0.611
AWCR	-0.352	-0.506	-0.449
DMR	0.380	0.045	0.306
WASTE	-0.195	0.861	0.294
RSH	-0.684	0.098	-0.380
RI	-0.616	0.031	-0.293

DMB= dry mass yield of branches; CRY= marketable roots yield; AWCR= average weight of marketable roots; DMR= dry mass content of roots; WASTE= waste yield; RSH= root shape; RI= resistance to insects.

Table 3. Estimation of expected gain (%) with direct (main diagonal bold), indirect (values above and below the main diagonal) and simultaneous (second part of the table) selections through the selection index of Mulamba & Mock (GSMM) and of the fuzzy inference systems, indicating selection gain for the HF system (GSMMHF/GSFZHF), selection gain for the AF system (GSMMAF/GSFZAF) and for the FIM system (GSMMFIM/GSFZFIM). Montes Claros, UFMG, 2021.

Variables	DMB	CRY	AWCR	DMR	WASTE	RSH	RI
DMB	**23.721**	-2.614	-7.123	0.826	0.741	-0.205	-3.155
CRY	5.916	**17.394**	-0.085	0.621	-0.170	-3.805	-1.111
AWCR	13.300	-5.365	**-9.715**	-0.138	0.381	-1.108	-3.217
DMR	0.022	-3.374	-3.055	**2.597**	-0.347	-0.837	-9.851
WASTE	13.289	3.517	-1.414	-0.648	**1.254**	2.330	9.931
RSH	5.101	1.412	-3.102	0.062	-0.377	**-10.151**	-12.831
RI	9.546	-2.106	-4.682	0.572	-0.054	-8.665	**-19.454**
GSMMHF	14.180	3.930	-6.134	1.337	-0.285	-7.318	-14.857
GSFZHF	7.448	13.656	-1.196	0.826	-0.122	-5.809	-11.603
GSMMAF	16.345	10.921	-2.885	0.020	0.682	-0.448	2.102
GSFZAF	21.472	8.809	-5.619	-0.625	1.218	0.816	3.884
GSMMFIM	19.672	3.377	-6.011	1.634	0.485	-4.942	-12.538
GSFZFIM	10.516	14.459	-4.925	0.983	0.199	-4.155	-10.437

DMB= dry mass yield of branches; CRY= marketable roots yield; AWCR= average weight of marketable roots; DMR= dry mass content of roots; WASTE= waste yield; RSH= root shape; RI= resistance to insects.

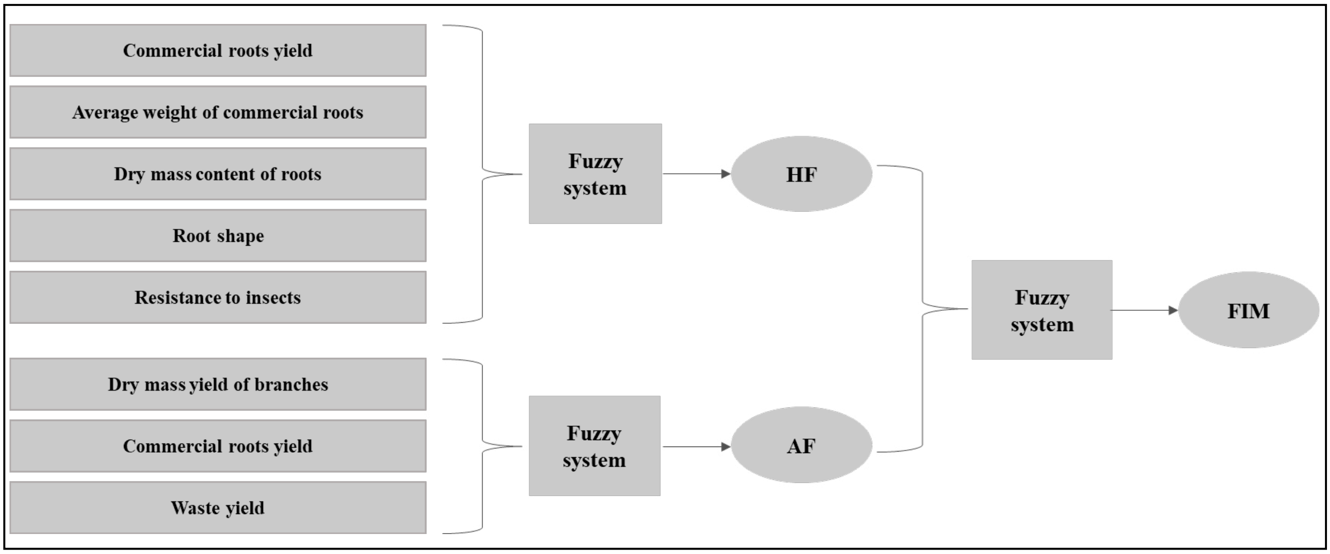

Figure 1. Fuzzy inference systems used as selection indexes for human feeding (HF) and animal feeding (AF) and for all criteria simultaneously (FIM) in sweet potato genotypes. Montes Claros, UFMG, 2021.

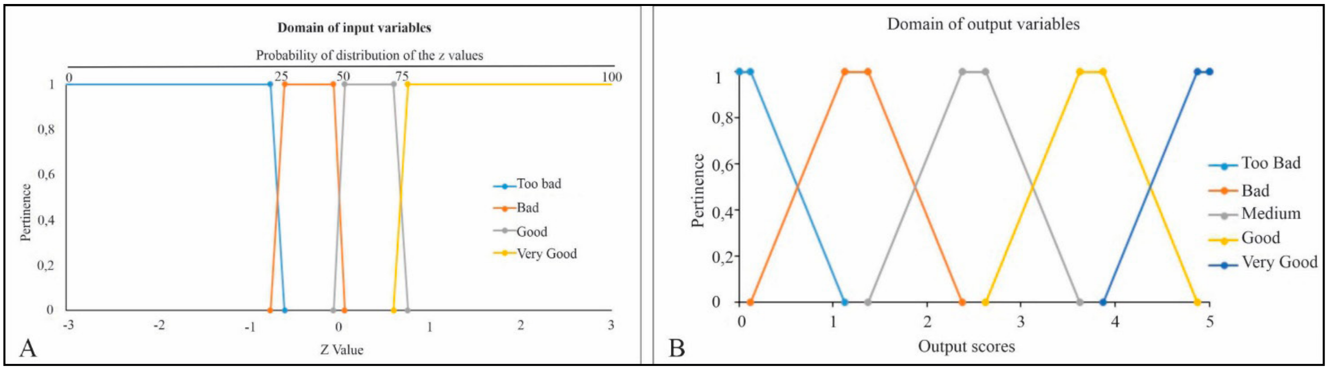

Figure 2. Definition of parameters a, b, c and d for the input variables (A) and for the output variables (B) of the created fuzzy systems. Montes Claros, UFMG, 2021.

It is possible to notice that the fuzzy system presented greater gains for DMB (21.472%) and WASTE (1.218%), while the Mulamba & Mock index presented greater selection gain for the production of marketable roots (CRY=10.921%) (Table 3).

The selection gains obtained by the Mulamba & Mock index and by the fuzzy system were similar for the FIM system, with the Mulamba & Mock indices showing superior gains in most traits. However, the fuzzy system allowed a greater gain for the production of marketable roots (14.459%), which is the most important characteristic for the improvement of the crop.

By means of the fuzzy logic, one can select the best genotypes with potentials for use in human and animal feeding, considering the scores obtained for each system in each genotype, being: UFVJM 07 (3), UFVJM 05 (11) , UFVJM 09 (19), UFVJM 40 (15), UFVJM 01 (16), UFVJM 25 (1) and UFVJM 15 (6).

By defining the rules and linguistic variables in the fuzzy logic, it is possible to prioritize the characteristics according to the interest of the breeder. In this work, CRY and RI were prioritized for human food related traits. This explains the greater gains obtained by fuzzy logic in these traits when compared to the MM index. For animal feeding, dry matter content of branches and leaves and WASTE were considered to be more important, allowing greater gains than the MM method. This assignment of different weights by the fuzzy method presents itself as an advantage over the Mulamba & Mock method.

In addition, the techniques associated with fuzzy logic allow the interaction and adequacy of data by the specialist, enabling to obtain results in a shorter time, compared to traditional methodologies (Mushtaq *et al.*, 2016). Allowing efficient analysis of a large amount of distinct information simultaneously without significant loss in selection (Mushtaq *et al.*, 2016). What highlights the multidisciplinary nature of the developed methodology, as it also allows the simultaneous analysis of quantitative and qualitative data (Pang & Bai, 2013; Casillas *et al.*, 2013). This feature reinforces the efficient compilation of distinct characters in a single system, called FIM, proving to be a useful and promising tool for genetic improvement programs (Carneiro *et al.*, 2018).The fuzzy systems developed were able to select sweet potato

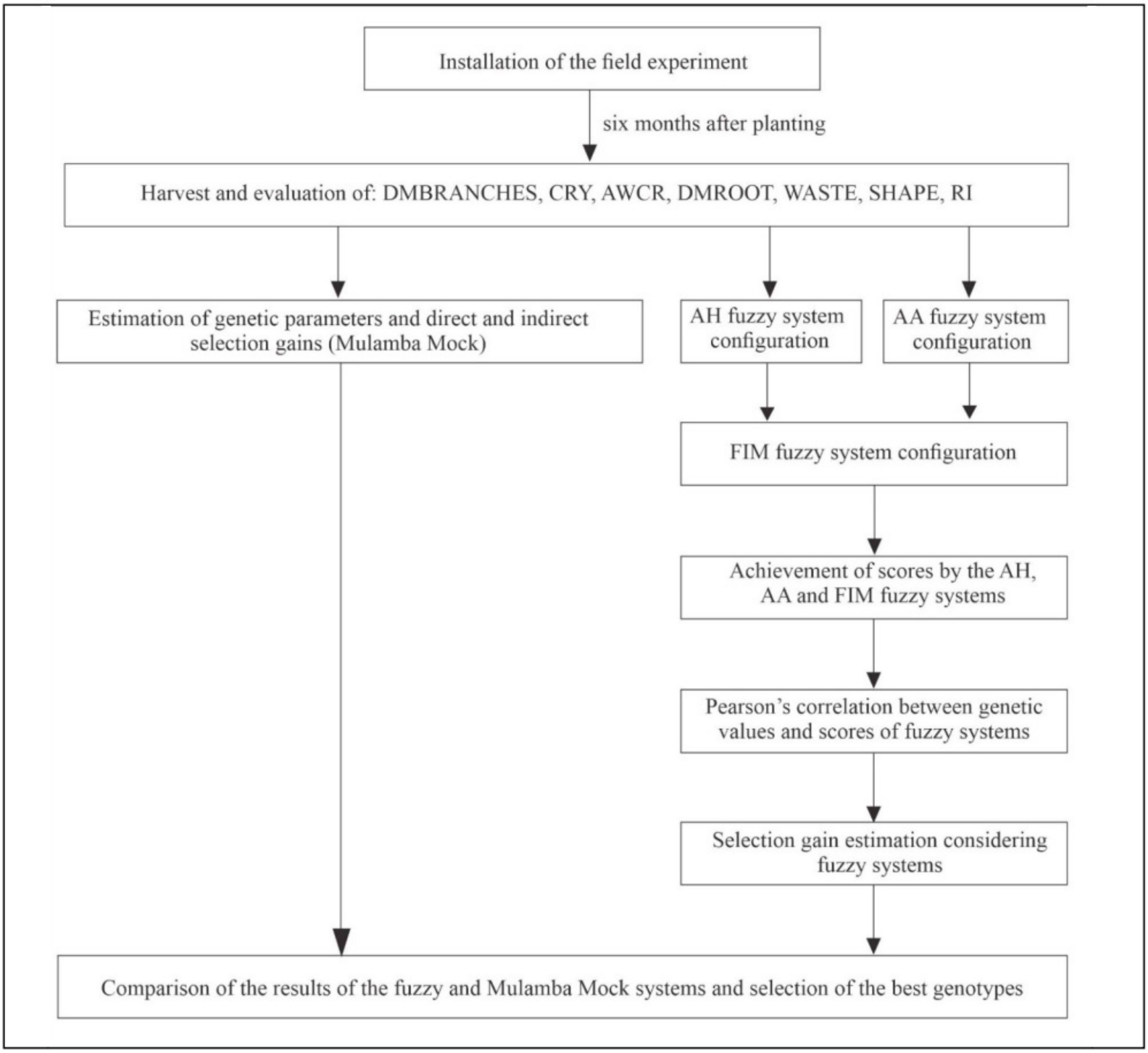

Figure 3. Diagram representing the methodology used for data analysis. Montes Claros, UFMG, 2021.

genotypes, with possibilities for use in human and animal food: UFVJM 07 (3), UFVJM 05 (11), UFVJM 09 (19), UFVJM 40 (15), UFVJM 01 (16), UFVJM 25 (1) and UFVJM 15 (6). In addition, fuzzy logic is common to modeling predefined commercial breaks for the crop, by incorporating the breeder's specialized knowledge. Thus, the developed fuzzy systems were efficient in the simultaneous selection of sweet potato genotypes, allowing a selection of plants closer to the best ideotype than the conventional Mulamba & Mock method.

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